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An examination of the effects of ride-hailing services on airport parking demand

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Abstract

The emergence of ride-hailing services offered by the Transportation Network Companies (TNCs) globally are substantially affecting how we travel by car, and as such, use parking facilities. Airport parking, which is a substantial source of revenue for the airports, is no different and anecdotal evidence suggest a reduction in parking revenue in airports in recent years as a result of the popularity of ride-hailing services. This research investigates the effects of the entry of ride-hailing services on airport parking patronage using three large airports (John F Kennedy International, Newark Liberty International and LaGuardia) in the US as a case study. Intervention analysis technique was used on time series monthly parking data at these airports, controlling for passenger numbers. Results indicate there was a statistically significant reduction in the numbers of cars parked at all three airports since the introduction of ride-hailing services, confirming the anecdotal evidence. Findings have implications not only for airport business and revenue models, but also for wider effects of ride-hailing and automation.

Keywords

Ride-hailing; on-demand mobility services; airport; parking; land-use; Uber; autonomous vehicles; TNC

An examination of the effects of ride-hailing services on airport parking demand

1. Introduction

The ride-sourcing or ride-hailing services provided by the Transportation Network Companies (TNCs) such as Uber, Lyft, Didi-Chuxing, Ola or Grab have gained rapid popularity among the global urban population, both in the developed and the developing countries. These on-demand mobility services use advanced information and communication technology based smart-phone applications to dynamically and efficiently connect drivers to consumers in real time (Shaheen et al. 2015). Unlike the traditional taxi services, often the drivers use their own vehicles to provide the service and are directly responsible for the capital and running costs of the vehicles. These services often operate under a more lax regulatory environment than taxis and pass on a substantial burden of the risk to the drivers, allowing them to be significantly cheaper than taxis in most places. The use of mobile phone applications with real-time and visual tracking of the vehicle and the absence of cash transactions (in some developing countries, cash can be used) make the TNC services convenient for the passengers too. The potential introduction of fully automated vehicles is expected to reduce the costs of these on-demand mobility services even further in future, with the possibility of a substantial switch from vehicle ownership to these on-demand mobility services. This has large implications on how we travel in future and consequently on energy use, carbon emissions, land use pattern and distributional equity. One lens through which potential impacts of vehicle automation could be understood is through studying the effects of ride-hailing services.

Even without automation, ride-hailing services are significantly changing the urban travel pattern. (Henao and Marshall 2018, Clewlow and Mishra 2017, Schaller Consulting 2018, San Francisco County Transportation Authority 2018). One area where ride-hailing services can have a profound impact on is the land-use, especially through reducing parking needs and potential repurposing of parking spaces in urban areas. Anecdotal evidence suggest that parking revenue in urban areas has been declining due to the emergence of the TNCs (Moris 2018). A recent survey among the parking professionals reveal that ride-hailing services are the largest driver of changes in car parking behaviour (International Parking Institute 2018).

Outside of traditional parking-centric businesses, parking plays a substantial role in the airport business. Parking is a large source of revenue at the airports, and often the largest non-aviation related source. Median gross parking revenues were USD 63 Million and USD 23 Million in large and medium hub airports in the US in 2016 (Mandle et al. 2017), while in London Heathrow Airport

(LHR), parking revenue was GBP 107 Million in 2015 (Steer Davies Gleave 2017). In San Francisco International Airport (SFO), parking and ground transportation account for around 14% of the operating revenue (Airport Commission 2018), while the share is 16% for the LHR (Steer Davies Gleave 2017). On the other hand, the use of TNC services for airport access has grown rapidly: at SFO, the use of ridehailing services increased by 59% between July 2016 and June 2017. While most of this growth came at the expense of commercial surface transport (primarily traditional taxis), there were substantial reduction (7.9%) in parking during that period, too. Such large reductions in parking transactions due to the operations of TNC services can cause significant concern for airport operators. However, apart from Henao et al. (2018), all of the evidence on the impact of these on-demand mobility services on airport parking are from the grey literature: there is little information on the background data (often using confidential commercial data that researchers do not have access to) or on the adequacy and robustness of the methods, making them less transparent to scrutiny. As such, this research aims to model the effects of ride-hailing services on airport parking using publicly available time-series parking data from three large airports in the US serving New York City: John F Kennedy International (JFK), LaGuardia (LGA) and Newark Liberty International (EWR). Unlike the previous scant literature on the topic, focus is on developing robust time-series models to understand the impacts.

The paper is organised as follows. Section 2 discusses the literature on airport ground access and impacts of TNCs on airport parking, while section 3 discusses potential data sources and data used in this research. Section 4 presents the econometric modelling detail. Section 5 discusses the results while section 6 concludes.

2. Literature on Transport Network Companies and airport parking

2.1 Airport surface access and Transportation Network Companies

Airports are often accessible by a multitude of modes: private cars, taxis, trains, underground rail, buses, dedicated shuttles, limousines and long-distance coaches (Pasha and Hickman 2016). Given the ease of access is an important consideration in air traveller’s choice of airports (Hess et al. 2013, Pels et al. 2003), airport access is a well-researched area. These studies primarily focus on descriptive statistics (share of different modes and the management of ground access, e.g. Ison et al. 2014) or discrete choice models to understand the importance of various factors in access mode choice (Harvey 1986, Pels et al. 2003, Akar 2013, Goakasar and Gunay 2017), and sometimes prediction of modal share, especially in the context of a new mode (Jou et al. 2011, Birolini et al. 2019). The key factors in air passengers’ access mode choice are similar to any other travel mode choice: journey time and journey cost (Harvey 1986, Pels et al. 2003), sometimes expressed as journey distance too (Psaraki and Abacoumkin 2002). Flexibility, reliability, safety, security and comfort are other important factors (de Neufville and Odoni 2003). Another factor that is possibly more important for airport access than other types of trips is the presence of luggage or ease of luggage handling (Bolland et al. 1992, Kazda and Caves 2008). Akar (2013) reports that air passengers also consider parking availability when deciding about airport access mode. There is substantial heterogeneity in the importance of these factors according to trip purpose and socio-economic characteristics (Pels et al. 2013), especially business users put more importance on travel time compared to leisure users.

Cars offer a direct door-to-door access which can often be the shortest distance (and/or shortest time), convenient and comfortable (no luggage transfer, own space), flexible, safe and secure. As such, cars often constitute one of the largest mode shares for airport access mode in most airports, if not the largest share. For example, cars, taxis and private hired vehicles (PHVs) were responsible for more than 85% of the modal share in UK airports without good rail connections in 2003 (Humphreys et al. 2005). A similar pattern is observed in the US too (Coogan et al. 2008). Therefore provision for ample car parking or parking management is an integral part of airport ground access strategy.

On the other hand, ride-hailing services (and taxis) can generally drop off at or pick up from curb-side or close, saving substantial time and inconvenience (e.g. carrying luggage) – especially since self-driven mid to long-stay car parks are often located the farthest from the airport and also require an additional transfer using shuttle services, which is perceived as inconvenient by the users. As such TNC services are increasingly gaining popularity over driving to the airports. Similar trend is observed in non-airport destinations as well – especially where parking is perceived as a concern (Clewlow and Mishra 2017, Henao and Marshall 2019). It is also documented that frequent long distance travellers – especially those who fly a lot for leisure – also use the ride-hailing services more compared to others, indicating the popularity of this innovative mobility service for airport access (Alemi et al. 2019). This hints at a potential reduction in the use of driving to reach the airports and subsequent reduction in parking demand at the airports.

2.2 Transportation Network Companies and parking

Parking (availability, costs, quality) is an important factor in mode choice – especially in urban areas. In reviewing the early literature on parking and travel demand, Feeney (1989) suggested that parking related factors could be more important than journey time or journey costs. While ride-hailing services have an obvious door-to-door advantage over the public transport modes and cost and convenience advantage over the traditional taxis, these services can also be more attractive than car travel in areas where parking is a concern. Indeed, 37% of ride-hailing service users cited limited parking at destination was a major factor in substituting car trips by ride-hailing trips in seven metropolitan cities in the US (Clewlow and Mishra 2017). The same study suggests that 39% of the ride-hailing service users would have used private cars in the absence of these services and as such would have required some form of parking at origins and destinations, which is no longer required for ride-hailing trips. Henao and Marshall (2019) put this number at 26%. As individuals switch from personal cars to ride-hailing services, it is expected that there will be aggregate observable effects on parking demand or parking business as well. There is some anecdotal evidence that the emergence of TNCs have substantially affected the parking businesses, especially in niche sectors like restaurants, event venues, bars and night clubs (Walker Consulting 2017, Henao and Marshall 2019).

The situation is similar with airport access and airport parking too. While there are a number of news reports on airports losing revenue due to the operations of ride-hailing services (Bergal 2017, AW 2018), academic research on the impact of ride-hailing services on airport parking demand is scarce. Henao et al. (2018) is an early academic work, which uses parking revenue at the airports as a proxy for airport parking. Notwithstanding the limitations of using revenue as a proxy for parking (see next section), Henao et al. (2018) had access to monthly parking revenue data and passenger numbers in 4 airports in the US (San Francisco (SFO), Denver (DEN), Kansas City (MCI) and Portland (PDX)). They plotted 12-month moving averages of monthly parking revenue per passenger and show visually that the revenue peaked between 12 to 24 months after the entry of TNCs in these airports after which they started to fall.

A few airport passenger surveys asked TNC users directly about their preferred alternative for airport access or egress in the absence of ride-hailing services. Analysis of two such surveys show that 21% of TNC users at SFO and 32% in Oakland International Airport (OAK) would have used private cars giving an estimate of the potential switch from private cars to ride-hailing services (Hermawan 2018). However, it is not known what share of these lost private car uses would have been parked at the airports or would be kerb side pick-up and drop-off trips and therefore the numbers represent an upper limit of the potential loss of parking custom. Mandle and Box (2016) report that around 18% of the ride-hailing service users at SFO previously used private cars for access (older data compared to Hermawan 2018), while Mandle et al. (2017) report that half of these private car use were likely to be parked, giving some estimate of the reduction in parking due to the ride-hailing services. In a different approach, Mandle et al. (2017) conducted a survey of US airport officials to suggest a self-reported reduction of parking between 5% and 10%.

A few grey literature use parking transaction data to provide a more direct insight. After controlling for passenger numbers, airport parking transactions in six unnamed US airports have declined by 0% to 13% as a result of TNC operations, indicating a varying level of impacts in those airports (Mandle et al. 2017). Walker Consultants (2018) found that ride-hailing services displaced around 3% to 5% of parking in an unnamed non-hub airport in 2015 and estimated an 11% reduction of parking transactions between 2014 and 2016 in another unnamed airport. San Francisco International Airport (2017) reported a reduction of 7.9% in total parking and 12.3% reduction in parking per passenger accompanying a 59% increase in the use of TNC services during 2016/2017. However, the airport was also facing parking shortage due to construction and parking fees were increased during the same period. The underlying data for calculating these numbers are often commercially sensitive and confidential and the methods employed are not transparent to the academic researchers (e.g. it is not known whether parking was steady or changing over time prior to the arrival of the TNCs). Henao et al. (2019) also use post-TNC parking transaction data to report that every three TNC trip reduces one parking transaction at Denver International Airport (DEN), while the ratio is five to two at Seattle-Tacoma International (SEA). However, they do not report the volume of reduction in parking demand. As such there is a need for a robust and transparent modelling of the effects of ride-hailing services on airport parking.

3. Data Description

3.1 Data types

There are three types of data that can potentially be useful in understanding the effects of the ride-hailing services on airport parking. Many airports conduct regular surveys of its passengers; these surveys often contain questions about their access and egress modes to and from the airport. While these surveys can give an estimate of modal share for access and egress and as such a switch from using car to the TNC services, often the passengers are not asked about whether they have parked the car at the airport, or whether they were dropped-off or picked up, which will not be captured in parking. Primary, targeted data collection through passenger surveys asking about alternate mode and parking behaviour is also possible, but expensive.

Parking revenue data over time can be another useful source. Often operational revenue breakdowns are publicly available in annual financial reports of the airports. However, it is quite common to aggregate the revenue categories and parking revenue can be grouped together with other sources of revenue (e.g. ‘parking and other’ in New York airports, ‘other fees’ in Los Angeles International Airport (LAX)). Also in the age of dynamic yield management to optimize parking revenue, relying on revenue data to proxy parking data can be misleading (e.g. parking number could fall as a result of increased parking fees, yet parking revenue could go up or vice versa). San Francisco International Airport (2017) indeed found that its parking revenue in 2016 had increased by 3% despite a reduction in parking demand of 7.9% as a result of increased parking fees during that time. Still, in the absence of other reliable data sources, Henao et al. (2018) used parking revenue data to show a reduction due to the emergence of the on-demand mobility services.

Because of the limitations in the two data sources above, we focus on the third, actual parking data from the airports. These parking data could be cross sectional in nature (many airports, some with TNC and some without), or time series (one airport, with parking data from pre-TNC and post-TNC days) or cross-sectional timeseries (several airports with timeseries data). While detailed airport parking data have recently been made available through 'open data' strategy of some cities (San Francisco, Los Angeles) these data often do not extend to pre-TNC days, making a before-after comparison impossible; these cities also have allowed TNC services so comparison between airports with or without TNCs are not possible either. As such we opt for using timeseries parking data over a period covering both pre-TNC and post-TNC days in select airports.

The Port Authority of New York and New Jersey (PANYNJ), publishes monthly parking numbers at each of its five airports on its website. Data for the three major airports, John F Kennedy International (JFK), Newark Liberty International (EWR) and LaGuardia (LGA) date back to 2003. This provides a useful time series data on parking at these airports covering both pre-TNC and post-TNC days. As such we use these airports as a useful case study.

3.2 Background of the airports

JFK, LGA and EWR together serve the largest city in the US, New York City. Geographically, JFK and LGA fall within the state of New York, while EWR falls within the state of New Jersey. The three airports and a smaller one, Stewart International Airport (SWF), are operated by the Port Authority of New York and New Jersey (PANYNJ). In terms of passenger numbers, JFK, EWR and LGA are individually ranked the 6th, 12th and 21st busiest airport in the US in 2018 (PANYNJ 2019). However, considering that all of these airports primarily serve the New York metropolitan area, this is the busiest airport system in the US, catering for a total of 137.8 M passengers in 2018. Of the three airports, LaGuardia primarily caters for domestic traffic (along with flights to Canada), while the other two are full international airports.

In terms of airport ground access, JFK and EWR have rail connections to regional and metropolitan rail network and access to these two airports by rail has been gradually increasing over the last 15 years (PANYNJ 2019). Despite serving fewer passengers, taxi trips to LGA is the largest of the three airports, resulting from the lack of a direct rail connection. Parking transactions and access by buses and motor coaches show a gradual decline in all three airports, although passenger numbers have been increasing during this time.

In addition to the ease of data availability for these airports, the New York airports represent an early case study for understanding the effects of the TNC services on airport parking. Outside of San Francisco, where Uber started its business, New York was the first city it expanded to. For Lyft, it was the third city. On the other hand, New York was also the first major city in the US to cap the number of ride-hailing vehicles in order to combat congestion resulting from the proliferation of the ride-hailing services. While recent data is difficult to come by, by the end of 2016, ride-hailing services were catering for around 350,000 trips per month at JFK and LGA (Anonymous 2019). This was around 75% as many as the traditional Yellow cabs from these airports – at a time when traditional taxis in all of New York metropolitan still had a similar market share as the TNC services. Given the ride-hailing services in May 2019 served 2.75 times as many trips as traditional taxis in metropolitan New York (Schneider 2019), it is safe to assume that their share in airport surface access has grown even further. These changes are not unique to New York: the rise of these on-demand mobility services has been rapid in many major airports in the world where they are allowed to operate, affecting both car parking revenue as well as passenger pick-up and drop-off operations by the traditional taxi and shuttle services.

Fig. 1 presents the monthly number of cars parked at JFK, LGA and EWR over time, which shows a gradual decline in the absolute numbers. This is despite a continuous growth of air passenger traffic, as shown in Fig. 2, but for the dip during the 2008 recession. Clearly, parking demand for all three airports show strong seasonality (Fig. 1), which is expected given air travel demand are also strongly seasonal (Fig. 2). The large dip in parking at LGA in late 2016 is due to a closure of a large parking lot for redevelopment.

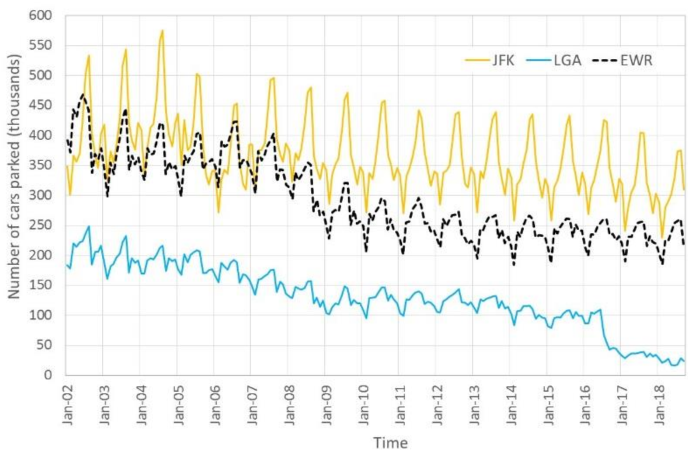

Fig. 1 Parking at three New York airports, source: PANYNJ (2019)

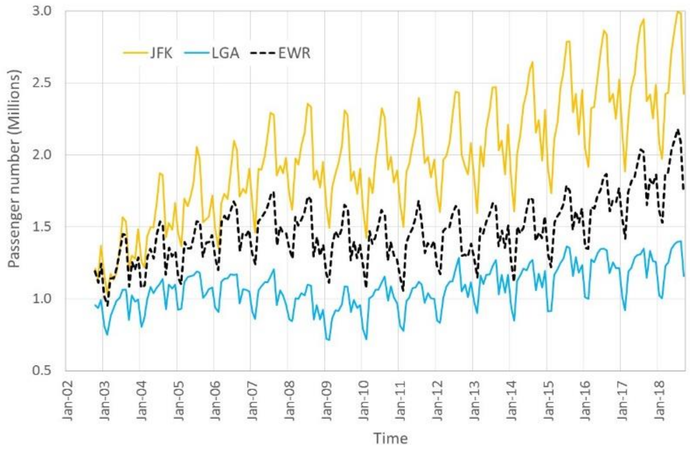

Fig. 2 Total departing passenger number at three New York airports, source: PANYNJ (2019)

4. Method for analysis

Given the time series nature of the parking dataset, our analysis follows an intervention analysis approach. Intervention analysis is widely used in order to model the effects of an external event on a time-varying variable of interest. There are several manifestation of the intervention analysis in econometric modelling. In the well-known Box and Tiao's (1975) approach, the variable is modelled in a univariate ARIMA (AutoRegressive Integrated Moving Average) framework and includes a transfer function in order to represent the pattern of response. The primary principle in this method is to develop a time series model using data until the intervention event, then forecasting future values of the variables for the post-intervention period and finally comparing the forecast values with the actual data during the post-intervention period. Often the transfer function is directly used to understand the nature of the effect. However it is not uncommon to model independently the difference between forecast and actual values of the variable during the post-intervention period to understand the effect in greater detail. Generally used with a univariate framework with the variable of interest in the model, external explanatory factors can also be added in these models.

Another method to model the impacts of an intervention is to use segmented multiple regression (Lagarde 2012) where the effect is estimated simultaneously along with the other parameters of the regression. This approach primarily introduces dummy variable(s) at the time of intervention, implying that the regression model parameters may have changed after the intervention, which are then estimated. In this approach, often the nature of the effect is assumed to be known (but can be tested): a simple dummy variable would mean a constant change in the value of the variable of interest, while the dummy variable multiplied with time will capture any effect that is changing linearly over time. Other interactions of the dummy variable with time variable is possible in order to capture non-linear effects. Dummy variable can be introduced with lags too, if it is believed that the impact will not start to materialize until after a few time periods after the intervention. The regression model will often be dynamic in nature in order to account for the temporal nature of the data. One risk is that in the presence of seasonality in the variable of interest and explanatory factors, the model could be a spurious one. Given the strong seasonality in the parking and airport passenger data, this is quite a possibility in this research.

In this paper we follow the more popular univariate approach to model the parking data over time. However, since the number of cars parked should be directly dependent on the number of passengers in the airport, we need to control for the number of passengers. We do this by normalizing car parking with respect to the number of passengers, i.e. our variable of interest is the ratio of cars parked to passenger number. Instead of total passenger numbers, we use departing passenger numbers, as we believe departing passenger numbers should be better correlated with parking compared to total passenger numbers. As such we model the ratio of cars parked to departing passenger numbers at each airport.

Uber launched its services in New York City in May 2011, although the less expensive and vastly more popular UberX service was launched in August 2012. On the other hand Lyft started operating in New York City much later in July 2014. In New Jersey, where EWR is located, Uber started operating in late November 2013. Since the changes in parking are expected to be slow and gradual, the expectation is that there will be a lag between TNC entry and the time when statistically discernible changes in parking can take place. For example, Henao et al. (2018) report that airport parking revenues start falling between 12 to 24 months after the entry of the TNCs. However we expect the direct impact on parking demand will have a shorter time lag compared to a reduction in parking revenue. As such we test two time points for each airport as the start of post-entry period: January 2013 and July 2013 for JFK and LGA, and July 2014 and January 2015 for EWR.

Our strategy therefore is to model parking per departing passenger (PP) in the following steps:

1. Estimate an ARIMA model for the variable PP using data until time T
2. Forecast PP for the periods after T
3. Compare the forecast PP with actual PP for periods after T, visually and using statistical tests
4. Calculate the average differences (if any) between the forecast PP and actual PP

In an ARIMA (p,d,q) forecasting model – popularized by Box and Jenkins (1978) – the variable of interest is modelled as a function of its own lagged values (autoregressive component) and lagged errors (moving average component). If the variable is non-stationary, then it is differenced until the series becomes stationary (a non-stationary timeseries is known to be integrated at order 1, if it needs to be differenced once to make it stationary), and then the autoregressive and moving average modelling is done on the differenced variable. The parameters p, d, and q represents the order of autoregression, integration and moving average terms, which are estimated. For this case – assuming a first order integration – the model to be estimated is:

$$\Delta PP_t = \sum_{i=1}^{p} \Delta PP_{t-i} + \sum_{i=1}^{q} \varepsilon_{t-i}$$

p and q can be continuous or discrete and are chosen on the basis of diagnostic tests.

5. Results

5.1 Graphical presentation

Fig. 3 presents the changes in the ratio of parking per departing passenger in the three airports serving New York City. Parking per departing passenger has been gradually declining over time, except for JFK, which shows some rapid decline around 2004-2006 period. This is a result of the opening of the Airtrain service connecting the airport to New York's subway system on December 17, 2003 (Stellin 2003), which has clearly caused a modal shift away from driving and hence parking. On the other hand, parking per departing passenger series for EWR shows two segments with different slopes, indicating the possibility of a structural change around the recession of 2008-2009 period. As such we use a smaller sample for intervention modelling at JFK (from July 2006) and EWR (from January 2009).

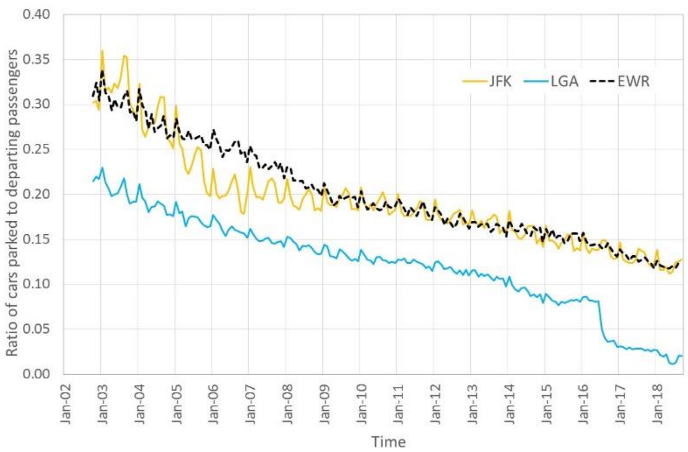

Fig. 3 Ratio of cars parked to total departing passengers at three New York airports, source: author's calculations

Like the parking and passenger data earlier, there is seasonality in the parking per passenger data too, but much less prominent than the other two. The seasonality arises possibly due to the differences in the types and purposes of air travel undertaken over the year, resulting in different types of travellers with different modes of access. For example, during the summer months, family travel for leisure will likely be a larger share of air travel compared to single person business trips, with vastly different access modes for these two trip purposes. The seasonality may also be a result of unavailability of parking during the peak travel periods since the parking supply is fixed.

Visually, it is difficult to discern any changes in the trends in Fig. 3 around the intervention period: January 2013 for JFK or July 2014 for EWR, although for LGA a mild dip slightly later around January 2014 is barely visible. Fig. 4 presents a 12-month moving average of parking per departing passenger for the three airports, which helps suppress the seasonality to reveal longer term trends. Once again the steep drop due to AirTrain in JFK is clearly visible, so is the change in slope in EWR around the 2008-2009 recession. However, apart from LGA, we cannot observe any clear deviation in the slopes for JFK and EWR after TNC introduction in these airports. Given the rather inconclusive nature of the graphical visualization, statistical modelling of the intervention become necessary.

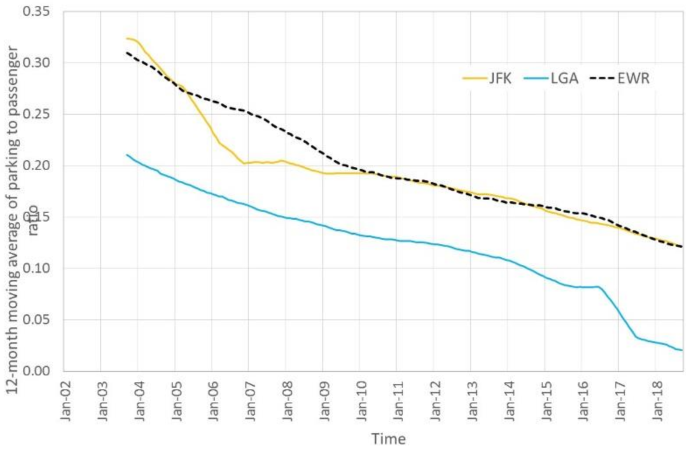

Fig. 4 12-month moving average of ratio of cars parked to departing passengers at three New York airports, source: author's calculations

5.2 ARIMA intervention model

Table 1 presents the results of the ARIMA (p,d,q) model for parking per departing passenger for all three airports. As mentioned earlier, the models are estimated using data for periods before the entry of the TNCs (strictly speaking, entry lagged by several months). The orders of the ARIMA (p,d,q) model are chosen on the basis of no autocorrelation, no partial autocorrelation and no unit root in the residuals. The residuals of the models selected are also tested for white noise characteristics in order to meet the underlying assumptions of ARIMA models.

Table 1 Parameter estimates for the ARIMA model before TNC entry

Model form	Model 1 (no transformation)			Model 2 (log transformation)		
Airport	JFK	LGA	EWR	JFK	LGA	EWR
	AR (3 12) I(1) MA (0)	AR (3 12) I(1) MA(1)	AR (12) I(1) MA(1)	AR (3 12) I(1) MA (0)	AR (3 12) I(1) MA(1)	AR (12) I(1) MA(1)
Constant	-0.0003	-0.0010***	-0.0006**	-0.0018	-0.0057***	-0.0033**
AR (3)	-0.0674**	-0.2418***	-	-0.0708**	-0.2498***	-
AR (12)	0.9090***	0.6671***	0.6589***	0.9046***	0.6217***	0.6523***
MA (1)	-	-0.6236***	-0.7908***	-	-0.7110***	-0.8028***
AIC	-597.62	-1008.99	-512.52	-341.45	-564.88	-286.34
BIC	-588.19	-994.97	-503.76	-332.02	-550.86	-277.58
DFGLS test for unit root in residuals	-7.432***	6.390***	-5.102***	-7.271***	6.819***	-5.127***
Phillip-Perron test for unit root in residuals	-68.23***	-96.24***	-53.69***	-69.47***	-95.98***	-54.31***
Bartlett test for residual white noise	0.746 (p=0.63)	0.801 (p=0.54)	0.882 (p=0.42)	0.707 (p=0.70)	0.826 (p=0.50)	0.840 (p=0.48)
Estimation period	Jul 2006 – Dec 2012	Nov 2002 – Dec 2012	Jan 2009 – Jun 2014	Jul 2006 – Dec 2012	Nov 2002 – Dec 2012	Jan 2009 – Jun 2014
N	78	122	66	78	122	66

[#] N is smaller in JFK to exclude the observations affected by the introduction of Airtrain and in EWR to exclude the pre-recession period, which shows different slopes

We have tested the regressions using log transformation and no transformation of the parking per departing passenger variable. Results of both of these functional forms are presented in Table 1. As mentioned earlier, we have modelled two temporal lags since TNC entry. For all three airports, the shorter lag tends to fit the data better. As such only those results are presented in Table 1.

Using the estimated parameters, parking per departing passenger is forecast for the periods starting January 2013 for JFK and LGA and July 2014 for EWR and presented along with the actual values in Figs. 5 to 7. Clearly, the forecast values based on the past-data are consistently larger than the actual values for all three airports. This shows that, after controlling for passenger numbers, parking in these three airports are smaller than they would have been in the absence of the ride-hailing mobility services. For JFK and EWR, the figures also clearly show that the differences between the forecast and actual values are increasing over time, indicating that the effects of the ride-hailing services are cumulative and not a one-time reduction. For LGA, the increase in parking per passenger from mid 2015 is due to the opening of a new parking lot (PANYNJ 2017), while the rapid reduction after July 2016 is due to the closure of a larger parking lot.

Table 2 presents paired t-tests to investigate whether the visual differences between the forecast values and actual values in Figs. 5 to 7 are statistically significant. All of the differences are statistically significant at the 99% confidence level, indicating parking demand had indeed declined since the entry of TNC services at these airports. While this statistical association does not absolutely prove causality, review of the past annual reports of the three airports did not reveal any other

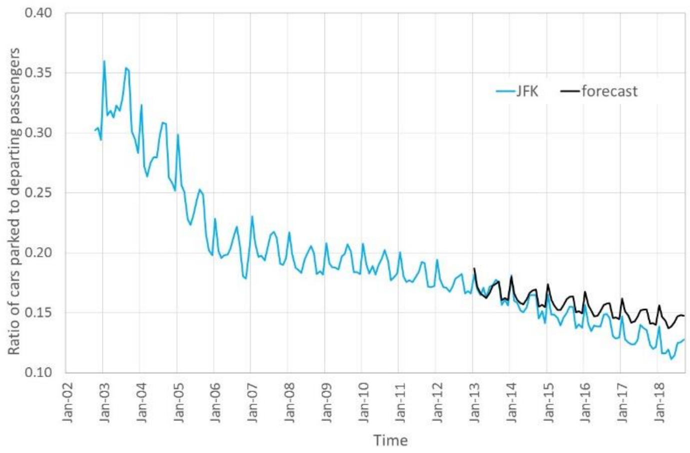

Fig. 5 Actual and forecast values of parking per departing passenger in JFK

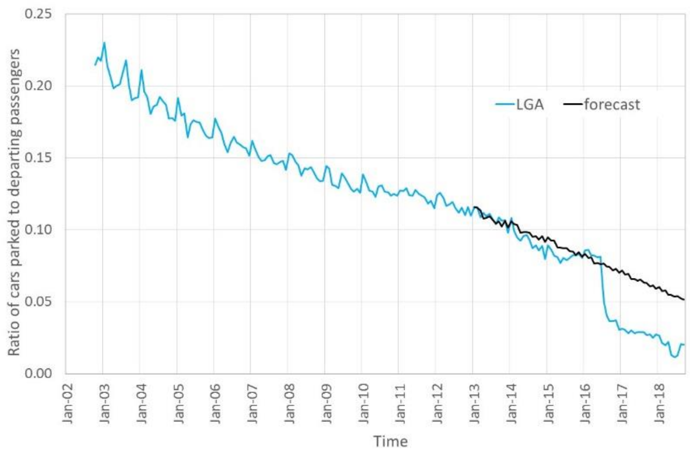

Fig. 6 Actual and forecast values of parking per departing passenger in LGA

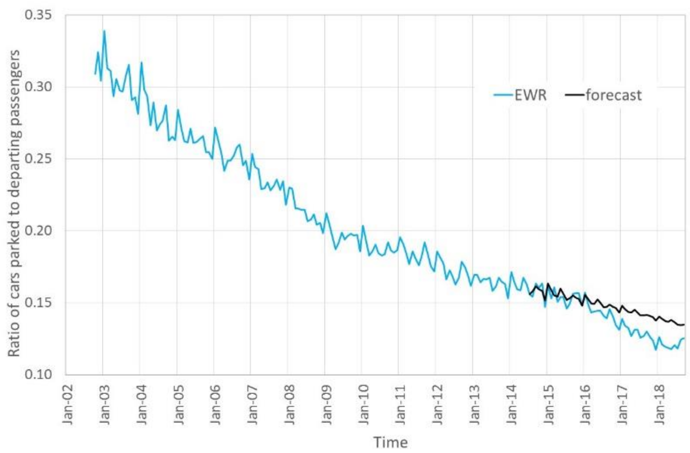

Fig. 7 Actual and forecast values of parking per departing passenger in EWR

major changes in ground access or parking facilities that could have consistently caused this reduction, leaving TNC entry as the most likely cause for the reduction. The mean difference is the largest for JFK and smallest for LGA, which is a consequence of having larger periods of observation for JFK and EWR with more time for the changes to take place. The test is done on a shorter period for LGA (January 2013 to June 2015) in order to avoid the confounding effects of opening and closing parking lots in July 2015 and July 2016 respectively.

Table 2. Differences between actual and forecast values (Model 1)

	JFK	LGA	EWR
Forecast period	Jan 2013 – Sep 2018	Jan 2013 – Jun 2015	Jul 2014 – Sep 2018
Mean of forecast values	0.1563	0.1007	0.1480
Mean of actual values	0.1451	0.0971	0.1401
Difference in means	-0.0112	-0.0036	-0.0078
t-stat (paired)	-11.28	-4.38	-7.95
One sided p-value	<0.0001	<0.0001	<0.0001
Difference in means for first 30 months after TNC introduction	0.0042	0.0036	0.0030

In order to compare the reductions in parking after controlling for the passenger numbers at the three airports, we recalculate the differences for the same number of periods since TNC entry. Given LGA offers the shortest number of usable observations – 30 months – this time period is selected for the common observation period. The results are presented in the last row of Table 2. Fig. 8 presents the per cent differences between actual and forecast monthly parking during the post-TNC period for all three airports. This confirms the findings of Figs. 5-7 that the differences are increasing over time. The trends of percent reductions for all three airports appear similar, too.

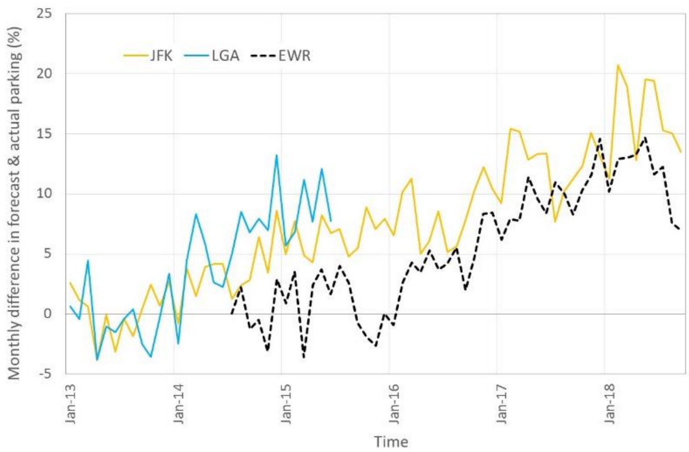

Fig. 8 Monthly difference in forecast and actual values of parking per departing passenger during post-TNC period

Airport operators and planners are naturally more interested in the absolute reduction in the number of parked cars that can be attributed to the emergence of the ride-hailing services. The parking per departing passenger forecasts are converted to parking demand forecasts by multiplying the ratio with actual departing passenger numbers. Fig. 9 presents these parking demand forecasts for post TNC periods with actual parking observed in the airports. Table 3 presents the actual and forecast parking demand in the airports for the entire post-TNC period for which we have data (except for LGA, which could be compared only until June 2015 due to reasons mentioned earlier). As can be expected from previous results, forecast parking demand is larger than actual demand. Ride-hailing services have so far resulted in a cumulative loss of around 1.87 M and 0.73 M parking transactions in JFK and EWR, once we consider the corresponding growth in passenger numbers during that period. This represents a *cumulative* reduction of 7.46% in 69 months at JFK, 5.71% in 51 months at EWR and 3.71% in 30 months at LGA. Considering only the last 12 months of our dataset (October 2017 to September 2018), the reductions are much higher – 15.6% at JFK and 11.6% at EWR. This shows a continued erosion in parking in these airports, as mentioned earlier.

Table 3. Differences between actual and forecast parking demand (Model 1)

	JFK	LGA*	EWR
Forecast period	Jan 2013 – Sep 2018	Jan 2013 – Jun 2016	Jul 2014 – Sep 2018
Mean monthly departing passengers	2,330,242	1,121,438	1,694,667
Post TNC parking forecast total	25,027,618	3,377,253	12,726,509
Post TNC actual parking total	23,159,981	3,251,712	11,999,494
Post TNC total reduction in parking	1,867,637	125,541	727,015
Post TNC total reduction in parking (%)	7.46%	3.71%	5.71%
Post TNC average reduction per year (%)	1.30%	1.48%	1.34%
Parking forecast last 12 months	4,330,067	-	3,100,535
Parking actual last 12 months	3,653,891	-	2,740,896
Reduction in the last 12 months of observation (%)	15.6%	-	11.6%

* LGA estimates are for shorter period, until June 2015

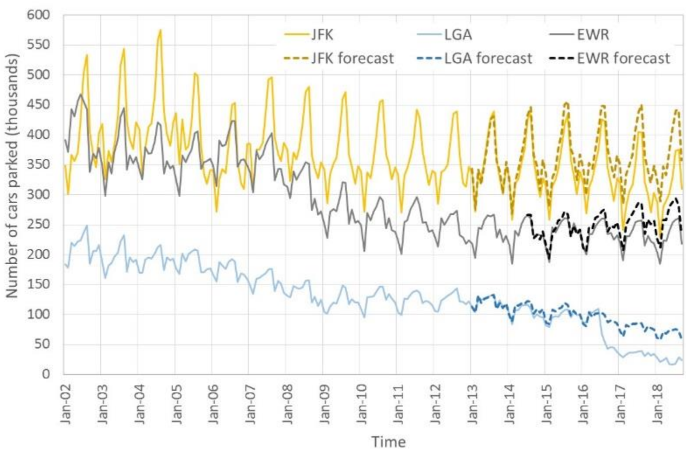

Fig. 9 Forecast and actual parking at the three airports

6. Conclusions

In this paper, we conducted intervention analyses to understand the effects of TNC entry on parking at three airports serving New York City. Using robust time-series econometric models on publicly available airport parking data, we show that – after controlling for passenger numbers and pre-existing downward trends – all three airports had a statistically significant reduction in parking patronage since the introduction of ride-hailing services. Our research thus supports the findings from the limited literature that the emergence of ride-hailing services had resulted in a reduction in car parking at the airports. Of the three airports, JFK and EWR had suffered a cumulative reduction in parking patronage of 7.46% and 5.71% since the emergence of ride-hailing services. During the last year of our data (October 2017-September 2018) the reductions were quite substantial: 15.6% and 11.6% respectively. LGA had several other concurrent changes that affected parking substantially, so the cumulative effects over the entire post-TNC period could not be disentangled.

The per cent reduction in parking is increasing over time in all three airports, indicating that the modal share for airport access has possibly not been stabilized yet. More importantly, the trends in reduction are not too different between the three airports, despite the airports having different initial modal share for surface access. While it is possibly too early to draw a generic conclusion from this trend, it will be useful to test in future if similar magnitude of reduction is observed in other airports of similar types, e.g. airports serving large metropolitans.

The reduction in parking patronage can have different implications for airport planning and operations. On one hand, there is a real risk of reduced revenue from car parking. While airports can use dynamic pricing to increase revenues even when the number of cars parked go down (e.g. as in SFO), there is also evidence of a reduction in parking revenue in several US airports a few years after the introduction of TNCs (Henao et al. 2018). On the other hand, the reduced demand for parking per passenger would mean that the airports can serve a growing air passenger demand and benefit from associated increases in revenue without having to construct additional parking lots (with associated savings in capital costs). This can be especially beneficial for airports constrained by a lack of space.

One potential area of future research is to understand how the impacts differ between long term and short term parking, which could be especially useful to parking operators for repurposing their lots. Especially, TNC services could have substantial cost and convenience advantages over long-stay parking at airports since these parking lots are generally located farther than the short-stay lots. The effects of other external and internal factors could also be incorporated in future if data become available – especially changes in parking prices in response to TNC operations and how that affected demand would be interesting to investigate.

Our results show airports stand to lose a significant amount of revenue through lost parking due to ride-hailing operations, yet airport operators have already taken measures to compensate for some of this loss, or even profit from the emergence of TNC services. Many US airports have already entered into business agreements with Uber, Lyft and other TNCs and recouped some of the lost revenue through a flat lump sum fee or entry charge for each drop-off and pick-up or a combination of both. For example, revenue from car parking at Los Angeles International Airport (LAX) was USD 97.6 Million in 2018, whereas the revenue from TNC operations – which was non-existent only a few years ago – was USD 44.3 Million (Martin 2019).

While our focus is not on the operations side, the increases in ride-hailing services for airport access would also likely require a different approach to kerb-side management at the airports. Many airports (e.g. George Bush International (IAH) at Houston or SFO in the US or Manchester International (MAN) in the UK) now have designated waiting lots for ride-hailing vehicles while others are planning to introduce ride-hailing pick-up and drop-off zones. In the UK, MAN has recently introduced a fee for all kerb-side pick-up and drop-off, including those made by private hire vehicles such as the ride-hailing services (Britton 2018). SFO also allows kerb-side pick-up and drop-off by TNC services for a fee, yet Logan International (BOS) at Boston has banned kerb-side operations of TNC vehicles. With autonomous or driverless ride-hailing services potentially set to disrupt urban travel and airport travel further, innovative business and operational models for the parking industry and ground access management for the airports will be required even more in future.

Beyond airports, parking control is an important car demand management tool used by the urban and city planners. A reduction in parking demand in the cities, which is also hinted by Henao and Marshall (2019), resulting from TNC operations would likely reduce the effectiveness of parking control as a measure to reduce car traffic in congested urban centres. With increased use of ride-hailing services, and the potential arrival of automated ride-hailing services increasing car travel even more in the future (Wadud et al. 2016), reducing vehicle trips and congestion can become a major challenge for city planners and regulators, who will left without one of their most effective demand management tools.

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